10862 Session 2022
A1 - ROTATING ELECTRICAL MACHINES
PS2 / Asset management of electrical machines

Automated tool for bearing fault diagnosis in induction motors, based on MCSA technique and machine learning algorithm

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SUMMARY

The induction motor (IM) certainly is the most implemented electrical machine in low voltage industrial applications. In order to extend its useful life, advanced techniques for predictive maintenance are required, mainly based on vibration data analysis, stray flux analysis, and advanced current analysis. Development of this kind of techniques is essential to not only prevent undesirable failures, but also to avoid unnecessary maintenance stops.

Many IM failures take place in the bearings, so they are critical elements for the machine. Nowadays, the vibration data analysis is the most typical technique used for bearing fault detection. However, advanced current analysis provides some advantages with respect to other diagnosis methods. Firstly, it is non-invasive, which means that current can be measured directly in the electrical panel; secondly, it can be applied during any operation scheme of the motor; and last but not least, it requires lower computational power and cheaper measurement equipment.

Advanced current analysis for IM condition assessment can be performed by two main methods, depending on the regime in which the analysis is applied. On the one hand, the classical technique is called Motor Current Signature Analysis (MCSA) and it is applied in steady state regime. On the other hand, there is the Advanced Transient Current Signature Analysis (ATCSA), which is applied in transient regime. Although the latest technique has already obtained satisfactory results, it is still under development.

The aim of this work is to develop an intelligent tool for bearing fault detection in IM, by combining the MCSA technique with machine learning algorithms for automated diagnosis. A test bench is designed to obtain the required IM measurements. MCSA technique, which is based on the Fast Fourier Transform (FFT), it is used to calculate the current harmonic spectrum, providing the fault patterns. Then, a supervised learning process is carried out through the application of Support Vector Machine (SVM) algorithm. The whole tool process has been programmed in Python environment.

Moreover, the developed tool is integrated in an Application Programming Interface (API), from where users can upload the motor current measurement, obtaining the bearing condition. Therefore, this API enables a remotely and effective monitoring for the IM bearings.

KEYWORDS

Induction motors, bearing fault detection, MCSA, SVM algorithm, machine learning, automated diagnosis.

1. INTRODUCTION

Electric motors are core elements in many industrial processes. According to some works [1], these machines can demand more than 40% of the energy generated in an industrialized country. Moreover, their use, which has been mainly focused on the industry, has recently expanded toward other sectors that are crucial for the sustainable development of today societies, such as electric vehicles. All these facts give an idea of the paramount importance of these machines and of their massive utilization.

The occurrence of failures on an electric motor can have very negative repercussions both on the reliability and on the efficiency of the industrial process in which it takes part: on the one hand, the presence of an unexpected fault may yield motor outages, causing undesired interruptions of the process with negative consequences (production downtimes, unplanned delays, repair costs…). On the other hand, the presence of failures or anomalies in the machine, even if it does not lead to immediate catastrophic effects, has a negative impact on the motor efficiency since, as previous works have proven [2], defects and anomalies in the motor increment its losses, yielding reductions in its efficiency. Thus, it becomes crucial to develop reliable systems to properly determine the health of electric motors.

IM are the most common electric motors typology in industry, since these are robust and reliable machines, and their cost is lower compared to other typologies. Despite this, these motors are prone to suffer different types of faults that have been deeply analysed in the literature. Among them, stator winding insulation faults and bearing failures are the most frequent failures, as several surveys have reported [1], [3]. These two faults may amount to near 80% of the total failures that can happen in an IM. Therefore, it becomes of capital importance to develop reliable condition monitoring approaches that are suited for the early diagnosis of those failures. Bearings are relevant elements that are subjected not only to their own degradation but also to those caused by the presence of other faults and anomalies in the machine (misalignments, eccentricities, rotor unbalances…), a fact that increments the stresses on them. Bearing faults may be caused by a diversity of causes, namely: defective mounting or assembly, overloads, lubrication problems, circulation of bearing currents…[4]. Problems in the bearings can even lead to a forced motor outage due to rotor-stator contacts, implying costly repairs. Therefore, it is essential to detect these faults when they are in their early stages of development.

Vibration data analysis is the most common technique to diagnose bearing faults. However, in some cases, vibration analysis is not conclusive for bearing condition monitoring purposes due to interference of other components caused by the load or other elements. In other cases, vibration analysis is not feasible due to the impossibility of installing accelerometers in the corresponding application. Over recent years, the analysis of motor currents has revealed itself as an excellent alternative to detect bearing failures [5], [6]. It has been proven that different bearing faults yield specific components in the Fourier spectrum of the current signal demanded by the motor. The identification and evaluation of the amplitudes of those components enables to determine the level of bearing failure. This approach is known as Motor Current Signature Analysis (MCSA) [1]. More recently, methods based on analysis of transient currents (ATCSA) have revealed as an interesting alternative to complement the MCSA conclusions in certain cases or faults for which MCSA analyses may lead to controversial results [7].

One pending issue of these methodologies is the fact that the diagnosis still relies on the necessity of a user that interprets the results of these methods and identifies the corresponding harmonics or patterns linked with the fault. This constraint limits the possibility of implementing these methodologies in autonomous systems aimed to determine the bearing condition. This work is intended to overcome these limitations by presenting an intelligent system for bearing fault detection in IM. The system combines the application of the MCSA technique with machine learning algorithms that enable the automatic identification and assessment of the fault harmonics, reaching a diagnostic conclusion without need of user intervention. The results obtained after application of the system to a specific testbench are described and prove the potential and versatility of the tool. The system opens a new broad of possibilities for maintenance engineers that are interested in obtaining a fast and reliable diagnosis of the condition of the bearings.

2. MCSA DIAGNOSIS METHOD

The advanced current analysis consists of applying mathematical processing tools to the current signal consumed by the motor, in order to obtain its frequency spectrum. The presence of harmonic components in certain frequencies, named as failure frequencies, allows to make a diagnosis of the motor condition. Such diagnosis can be done since the mechanical failures lead to a distortion of the motor magnetic field and, hence, the motor current. Depending on the operational regime where the signal processing is performed, two techniques can be defined:

- MCSA: the signal processing is applied during the steady state, when the power load and the motor speed are almost constant.
- ATCSA: the signal processing is applied during the transient state, specifically in the start-up, when the motor speed is variable.

In the present work only the MCSA technique has been used. This technique is based on the application of the Fast Fourier Transform (FFT), which provides the harmonic components included in the analysed signal. Therefore, by applying the FFT, the signal is converted from the time domain to the frequency domain. The harmonic components are defined by their magnitude and frequency.

Once the FFT is applied, the failure frequencies should be identified. In this case, the failures have been performed on the bearings, specifically on the external ring and the bearing balls. It can be demonstrated that this kind of mechanical failures cause the following failure frequencies in the vibrational spectrum [8], as shown in Table I.

Table I. Failure frequencies in the vibrational spectrum [8]

Failure	Vibrational frequency (Hz)
External ring	$f_0 = \frac{N_b}{2} \cdot f_r \cdot \left(1 - \frac{D_b}{D_p} \cdot \cos\beta\right)$
Bearing balls	$f_B = \frac{D_p}{D_b} \cdot f_r \cdot \left(1 - \frac{{D_b}^2}{{D_p}^2} \cdot \cos\beta^2\right)$

Where N_b is the number of balls, D_b is the ball diameter, D_p is the pitch diameter, f_r is the rotor mechanical frequency and β is the angle showed in Figure 1.

Then, the failure frequencies in the vibrational spectrum can be converted into electrical current frequencies through the following expression:

$$f_c = \left|f_s \pm m \cdot f_{0,b}\right|$$

Where f_s is the system frequency (50 Hz/60 Hz) and m is a natural number (1, 2, 3, …) which indicates the harmonic family group.

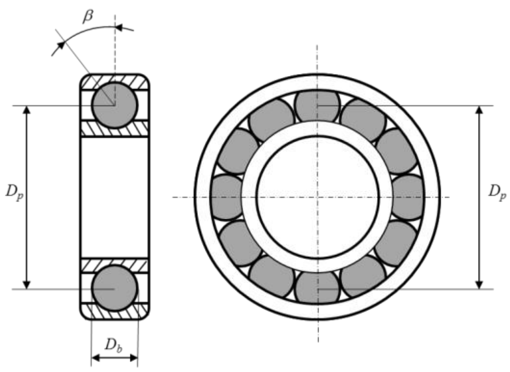


Figure 1 Bearing parameters

3. ALGORITHM FOR AUTOMATED FAULT DETECTION

With the aim of automatize the failure diagnosis process, an algorithm which detects both types of failures has been developed. In such sense, the algorithm has been developed based on machine learning techniques. With the use of this kind of artificial intelligence techniques, it is transferred to a machine the technical know-how to evaluate if there exists any failure in the motor under evaluation. Due to the type of data the failure detection methods work with, the developed algorithm is based on supervised learning techniques. Considering the size of the available dataset to develop the algorithms, it has been chosen a classification technique based on Support Vector Machines (SVM). This technique is able to perform both regressions and classifications. In this case, it has been used to classify the data between failure and non-failure after applying the MCSA method, explained in the previous section.

The SVM classification technique works classifying the input data into the available classes, specified by the labelled targets in the training dataset. To classify the data, it is divided into subsets which are placed in the broadest spaces as possible, based on its features. These spaces are determined by a separation hyperplane, defined as the support vector between the points of two contiguous classes. Based on the spaces, defined during the training process, when the algorithm works with new input data, this data is classified based on the spaces defined for each class.

During the training process of the SVM technique, apart from adjusting the parameters according to the obtained accuracy in each iteration, it is necessary to define the hyperparameters to fit the algorithm with the training data. The hyperparameters are defined as γ and C, and the whole formulation for an SVM algorithm is determined by expression 1. For a sample of n records, in which features are assigned to vectors $x_i \epsilon \mathbb{R}, i = 1, \dots, n$ and labels are assigned to y, following the restrictions (expressions 2 and 3) it is calculated the values of b which maximizes it.

$$max\left(\sum_{i=1}^{n} b_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} y_i b_i \left(e^{-\gamma}\left\|x_i - x_j\right\|^2\right) y_j b_j\right) \quad (1)$$

Where:

$$\sum_{i=1}^{n} b_i y_i = 0 \quad (2)$$

$$0 \leq b_i \leq C \quad (3)$$

The usual hyperparameters set up process consists in determine a set of possible values for each hyperparameter and check the accuracy of every possible combination of their values. The developed algorithm, instead of implementing the usual procedure to set up the hyperparameters, makes use of metaheuristic algorithm to set up hyperparameters, concretely the Particles Swarm Optimization (PSO). This algorithm searches a set of values between given bounded values for each parameter to be set and defines a value for each searched parameter which provides a maximum, or minimum, value of the cost function. In this case, the cost function for the PSO is the training process error of the algorithm to be trained, setting the PSO to minimize it. The use of this technique has improved the performance of the SVM algorithm usage to detect motor failures.

As the available datasets for each type of failure are narrow, two independent detection algorithms have been implemented for each type of failure, to ensure a better performance on the failure detection. Despite each algorithm is trained to detect different motor failures, their training process is the same, using the techniques previously defined. The implemented structure to train the algorithm is exposed in Figure 2.

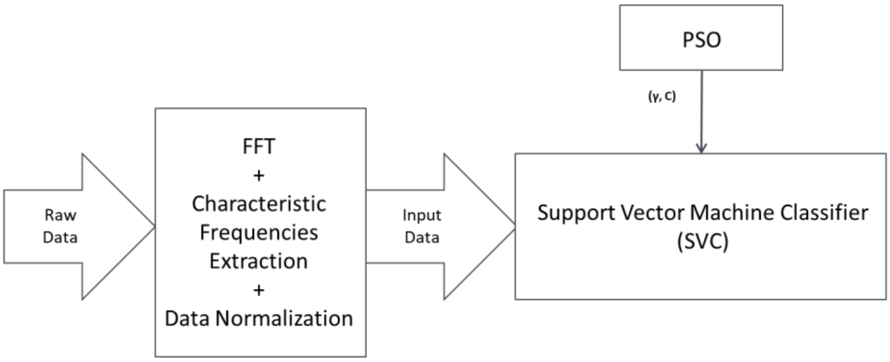


Figure 2. Structure of the failure detection algorithms

The developed algorithms have been implemented to take the current measurements as input data, obtained from the field tests. Once the input data is provided to the algorithms, the process follows the next steps:

- The current with time data is transformed to current with frequency data, by means of applying Fast Fourier Transform (FFT).
- Following the MCSA method, the characteristic frequencies of each failure are extracted.
- Characteristic frequencies data is normalized to make all the extracted features have the same impact on the training process of each algorithm.

Once the input data is obtained in normalized format, it is performed the algorithm training process, setting up the hyperparameters by means of the PSO technique, as it has been described previously. Finally, as result of the whole process, two different failure detection models are obtained, one for external ring failure detection, and another for bearing ball failure detection.

4. APPLICATION PROGRAMMING INTERFACE (API)

The interface of the web application is intended to remotely run the models explained in the previous section through an intuitive environment for the user. Web application interface communicates with the diagnosis system through API REST architecture within a .NET based application development. Figure 3 shows the interaction between different developments.

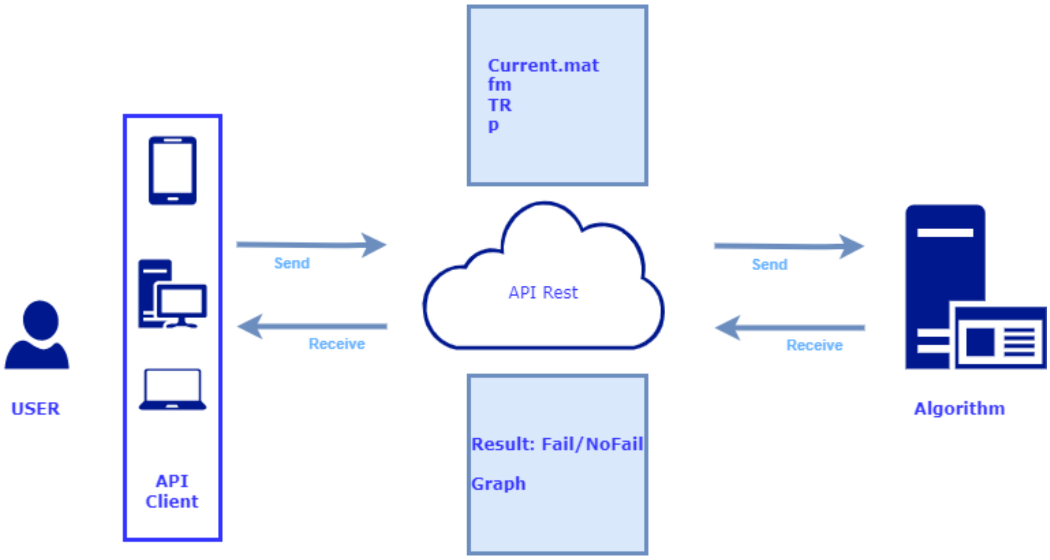


Figure 3. Block diagram interaction

A description of the different application screens is provided in the following lines:

- *Main screen*: It shows to all useful information about how many tests on the motor bearing has passed without fail or with fail at the application tool. In addition, the user could check total number of trials since the start of registration.

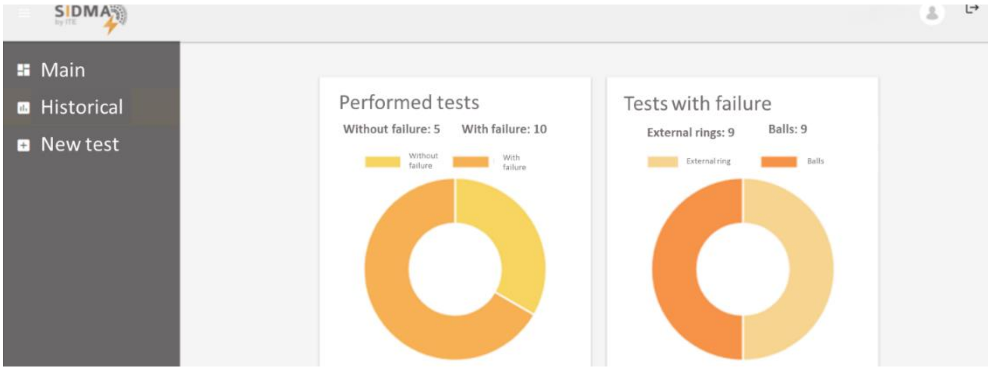


Figure 4. Main screen

- *New test screen*: API contains a new test page to configure all parameters. First the kind of motor bearing and the sampling values should be configured. Then, user should introduce the file with the engine current values vector, sampled frequency, bearing type and pole pairs.

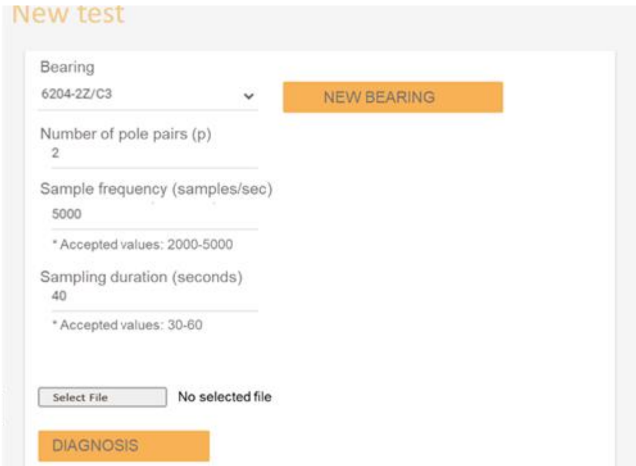


Figure 5. New test screen

- *Diagnosis result screen:* User obtains a Fail/NoFail response for external ring failure and bearing balls failures. Moreover, the FTT spectrum of the motor current is provided.

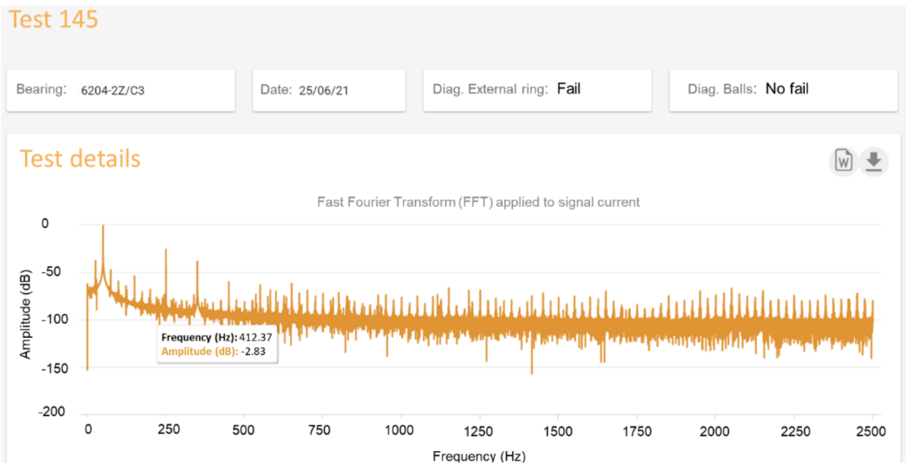


Figure 6. Diagnosis result screen

- *Historical screen*: For more user information, it could access to the historical diagnosis in order to review previous tests of the different engines.

5. EXPERIMENTAL TESTS

The aim of the experimental tests is to obtain real registers of the current waveform when the motor is working at health and failure condition in the laboratory. These registers are used as raw data for the algorithm supervised training. In this section, the test bench, the failure scenarios, and the operating conditions for measuring are described.

a) *Test bench:* The test object is a squirrel cage IM, whose rated features are showed in Table II:

Table II. Rated features of tests induction motor

Voltage (U)	Frequency (f)	Speed (V)	Power (P)	Current (C)	Cos ϕ
400Δ / 690¥	50 Hz	1435 rpm	1.1 kW	2.4 A	0.78

The test bench is formed by the following devices, which are connected as shown in the schema of Figure 7:

- AC induction motor: it is the test object where the failure is induced.
- DC motor: it acts as an adjustable load.
- Three-phase autotransformer: it controls the voltage applied to the AC motor.
- DC Source: it is formed by a single-phase autotransformer with a diode-based rectifier connected to the output. It controls the voltage applied to the DC motor.
- Resistors: they are connected to the induced terminals of the DC motor, with an overall resistance of 14 Ω.
- Switches: automatic breakers between the terminals of the AC autotransformer.
- Measuring equipment: three clamps connected to an oscilloscope for the AC motor current measuring and a multimeter for the AC autotransformer voltage measuring.

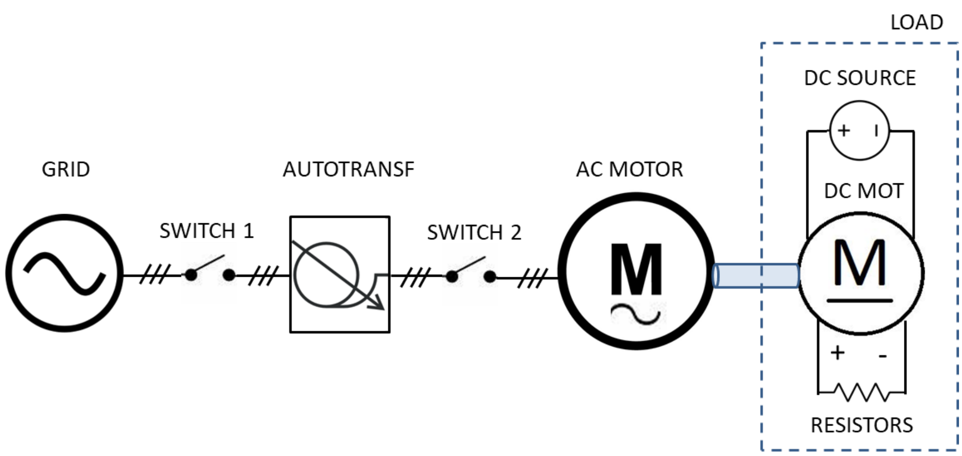
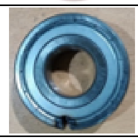


Figure 7. Schematic test bench

b) *Failure scenarios:* To reproduce real failures in the bearings (model SKF 6204-2Z/C3), three scenarios have been defined in the laboratory, which are described in Table III. The selected scenarios are repeated in a sequential manner using a large number of bearings for testing.

Table III. Failure scenarios

Scenario	Description	Picture
Healthy bearing	No damage is performed	
Cut bearing	A transversal cut is performed in the external ring	
Dirty bearing	Different kind of shaving is introduced between the balls	

c) *Operating conditions for measuring:* The MCSA technique requires the measurement of the current signal consumed by the motor. The current measurement has been performed using three clamps (one per phase) connected to an oscilloscope, which has been configured at 5000 samples/s of sample rate and 40 s of record length.

The operating condition of the motor group depends on two controlled variables:

- Voltage applied to the AC motor (U_{AC}): it is controlled by the three-phase autotransformer and it determines the starting torque of the AC motor.
- Voltage applied to the DC motor (U_{DC}): it is controlled by the single-phase autotransformer and it determines the load level.

By combining different values of the abovementioned variables, several operating conditions can be achieved. Specifically, four conditions have been defined, whose main features are showed in Table IV. The motor current is measured for each operating condition and failure scenario.

Table IV. Operating conditions for current measuring

Operating condition	U_{AC} (V)	U_{DC} (V)	Description
1	100	0	Not loaded AC Motor at minimum voltage
2	200	0	Not loaded AC Motor at medium voltage
3	200	70	Loaded AC Motor at medium voltage
4	400	90	Loaded AC Motor at rated voltage

6. RESULTS

The models integrated in the API has been trained by using a large quantity of laboratory trials. As a result, the API can detect potential failures located in the bearings of IM. In order to assess the API performance, a new set of IM have been damaged. In this section, the API output screen is showed for each scenario defined in Table III. The obtained success percentage of the diagnostic tool is near 70.1% for the external ring failure and near 70.9% for the ball failure. Both percentages could be increased if more laboratory trials would be done.

It should be noted that the user is not able to observe the fault patterns in the FFT image provided by the API, since there are no appreciable differences between healthy and faulty graphs at first sight. The diagnosis result is performed autonomously by processing the internal data.

a) *Healthy bearing:* No damage is induced in the bearing, so the diagnosis result is negative for the external ring and the ball failure (see Figure 8).

Figure 8. Diagnosis result for a IM with healthy bearing

b) *Cut bearing:* Damage is induced in the external ring, so the diagnosis result is positive for the external ring and negative for the ball failure (see Figure 9).

Figure 9. Diagnosis result for a IM with cut bearing

c) *Dirty bearing:* Damage is induced in the bearing balls, so the diagnosis result is negative for the external ring and positive for the ball failure (see Figure 10).

Figure 10. Diagnosis result for a IM with dirty bearing

7. CONCLUSIONS

In this paper, an intelligent detection system has been developed to diagnose failures in the external rings and the balls of IM bearings. This tool is based on the MCSA technique, which is an innovative method for the application of bearing failure detection. It also includes a machine learning algorithm based on support vector machine (SVM), which has been trained with real current registers from laboratory testing. Thanks to this algorithm, the detection system is capable to perform an automated diagnose of the motor bearing status, with an approximated overall accuracy of 70%; specifically, 70.9% for external ring failure and 70.1% for bearing balls failure.

Moreover, the intelligent detection system has been integrated within an application programming interface (API), which can run the algorithm remotely through any authorized computer. This API provides a friendly environment to facilitate its use for any unexpert user. Therefore, if the users have the suitable equipment for the current measurement, they can easily obtain a rapid diagnose of their motors by using the API. In any case, the API developed in this paper can be used as a support tool in the diagnose decision-making process, improving the quality of the motor maintenance and, hence, extending the useful life of these machines.

As future works, the obtained errors for bearing failure detection can be reduced by using more current registers in the algorithm training process. Besides, more detection models could be integrated in the diagnosis system in order to cover other common failures in IM, such as rotor misalignment, broken rotor bars, load coupling failures, and so on. As a result, an automated diagnosis system, which covers the most common mechanical failures detection in IM, would be obtained.

ACKNOWLEDGEMENTS

The authors acknowledge the contribution of co-financing by the Institut Valencià de Competitivitat Empresarial (IVACE) and the European Commission (through the European Regional Development Fund (ERDF)) for making possible the development of SIDMA project (IMDEEA/2020/103), allowing the Instituto Tecnológico de la Energía (ITE) to disseminate the results of research conducted and to facilitate and promote the transfer of knowledge to companies of the Valencian Community.

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